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Impact of Rainfall Shocks on Child Health: Evidence from India*

Vibhuti Mendiratta†

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Abstract

While there is evidence of discrimination against girls in the allocation of resources within a household under normal circumstances, it would be worthwhile to explore the effect of extreme conditions such as rainfall shocks on the outcomes of surviving girls and boys. In this paper, I estimate the impact of rainfall shocks in early childhood on the anthropometric outcomes of girls and boys aged 13-36 months in rural India. I find that adverse negative rainfall shocks (in utero and first year after birth) negatively impact height for age and weight for age for both girls and boys. Further, I explore two channels through which rainfall affects child health: by affecting the relative price of parent's time in childcare and through income (as rainfall generates variation in income through its effect on agricultural output). I find that positive rainfall has a positive effect on agricultural yield and arguably income in India. This is further supported by the finding that negative shocks are harder to insure in poorer states and poorer households as reflected by the poor anthropometric outcomes of children.

Keywords: Anthropometric outcomes, Rainfall, India.

JEL Classification: I12, Q54.

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1 INTRODUCTION

The relative status of women in the developing world is poor, compared to developed countries. The literature has highlighted the existence of gender inequalities in South Asia, attributed to strong preferences for male child, often the result of traditional customs. Further, households in India, as in much of the developing world, face substantial risk - an inevitable consequence of engaging in rain-fed agriculture in a drought prone environment. This further affects the ability of households to provide for their families and invest in children. Investments in children and human capital are central to enhance the well being of households, break the intergenerational transmission of poverty and finally lead to the growth and development of a country.

The phenomenon of 'missing women', a term coined by Amartya Sen, was used to describe that the gender ratio is much lower than would be expected if women and men were subject to similar allocation of resources in a household (Sen, 1990). The comparative neglect of female health and nutrition, especially but not exclusively during childhood, is largely responsible for such a phenomenon. Indeed, the most striking evidence on skewed sex ratios and gender bias in mortality comes from South Asia in general and India in particular. According to the gender statistics of the Census of India in 2001, out of the total population of India, 532 million or 52 percent are males and 497 million are females constituting the remaining 48 percent in the population. In sheer numbers, males outnumber females by 35 million in the population. Further, Kynch and Sen (1983) explain the sex ratio by pointing out that "except in the period immediately following birth, the death rate is higher for women than for men fairly consistently in all age groups until the late thirties. This relates to higher rates of disease from which women suffer, and ultimately to the relative neglect of females, especially in health care and medical attention".

Given the literature on comparative neglect of women in India, one would expect to find evidence of discrimination against girls in the allocation of resources within a household under normal circumstances. The literature addressing this topic is mixed (Deolalikar and Rose, 1998; Subramanian, 1995; Subramanian and Deaton, 1990). Moreover, it is conceivable that under abnormal circumstances like shocks faced by households, parents alter their behaviour in a way which leads to discrimination against girls. Indeed, past research has provided us with some evidence that abnormal circumstances matter. For example, Rose (1999) establishes that mortality among girls in higher in the presence of a rainfall shock as compared to boys in India.

In a similar spirit, we assess the impact of rainfall shocks on the health of surviving children and explore gender differences. To measure the impact of rainfall on child health, we use data from the second round of Demographic and Health Survey conducted in 1998-99, and link it to district level historical rainfall data for India. We examine the effect of weather shocks in utero and early childhood on anthropometric outcomes of children aged 1-3 years living in rural India. We find that children are very vulnerable to rainfall shocks in the first year of birth and in utero as reflected by the poor height for age and weight for age Z scores. We do not find a differential impact of negative rainfall shocks on boys and girls and the results remain robust to the inclusion of month of birth fixed effects and other variables. It must be mentioned that the findings of Rose (1999) have some implications on our analysis in that we are comparing a healthier sample of (surviving) girls with an average healthy sample of boys; thus pointing that our findings are lower bound estimates of real causal impact. In addition, we also find that the results are heterogeneous in that children living in poorer states, poorer households (in terms of wealth) and girls with uneducated mothers have a harder time smoothing consumption with bad rainfall years as reflected by poorer anthropometric outcomes.

We identify three channels through which rainfall shocks could affect child health - income, time spent by parents in childcare and spread of water borne diseases. Using the World Bank India Agriculture and Climate dataset, we check the impact of rainfall on agricultural yields of major crops in India and find that negative rainfall shocks do reduce yields of 4 out of 5 major crops in India. Thus, negative rainfall represents a clear decline in income of Indian agricultural households. In addition, more or less rainfall also has an impact on time spent by parents in childcare. Using time use data in Rural Economic and Demographic Survey data from 1998-99, we establish that mothers aged 15-30 years are indeed more likely to take up market work in districts that experienced bad rainfall in the wet season of 1998. Whether this translates into less time in childcare is unclear and we do not have time use data to check it. But we check the impact of rainfall directly on childcare activities such as breastfeeding and vaccinations. One of the ways this channel could manifest itself is if the mother is more likely to wean children from breastfeeding during good rainfall season (as rainfall affects demand for parent's labour on the farm). We check for this channel by looking at the direct impact of rainfall on the risk of termination of breastfeeding by the mother and find no effect. We also find no effect of rainfall shocks on the likelihood of being vaccinated except that boys are less likely to get the first polio vaccination in the presence of positive rainfall. The third potential channel is through the spread of water borne diseases such as malaria, however evidence indicates that there is very little mortality due to malaria among 0-4 year old children with boys being more prone to die than girls (Dash, 2009).

This paper contributes to the literature on the investigation of gender bias in India. Previous studies have shown gender based differences in mortality while evidence related to anthropometric outcomes and allocation of resources (food,nutrient, medical care etc.) is mixed. This paper contributes to the literature by finding no gender based discrimination in the face of shocks. We do not find that the household changes the intra household allocation (in terms of nutrition, medical care, breastfeeding practice among others) to the disadvantage of the girl so that it leads to deteriorated health outcomes for her, as measured by anthropometric outcomes. In addition, we check for possible mechanisms through which shocks could affect child health outcomes.

The paper is organized as follows. Section 2 discuss the associated literature, Section 3 sets the conceptual framework. Section 4 describes the context of India and the data we use. In Section 5, we describe the econometric specification. Estimation results are reported in Section 6 and Section 7 concludes.

2 LITERATURE REVIEW

In India, child sex ratio (0-6 years) of the population has been registered as 914 in the 2011 Census (refer to Figure 1). This ratio has been continually declining from 927 in 2001, 945 in 1991 and 962 in 1981 (refer to Figure 2). Another notable feature is that child sex ratio has fallen below the sex ratio at birth according to the Census of India 2001. The child sex ratio was similar to the sex ratio at birth before 2001. But between Census 1991 and Census 2001, 31 States / union territories reported a decline in Child Sex Ratio. This is a reflection on the status of the girl child in the country and further points towards investigating the existence and causes of gender bias during infancy and early childhood among surviving children. That said, evidence on the existence of gender bias in nutritional status in India is mixed (Basu, 1989, 1993; Mishra et al., 1999; Ryan et al., 1984). However under abnormal circumstances such as income shocks, the story might change. Thus, it would be worthwhile to explore if female children bear the excess burden in the face of shocks when households are unable to smooth consumption. This is the question I seek to address.

Several studies have found higher mortality among girls relative to boys in South Asia (Sen, 1981); (Dreze and Sen, 1991; Sen, 1988). These include largely descriptive accounts like the one by D'Souza and Chen (1980) which provide conclusive documentation of higher female over male mortality shortly after birth through the childbearing ages in rural Bangladesh. Another influential account has been provided by Das Gupta (1987) who argues that in Punjab, gender bias in mortality is more severe for daughters who are born into families with other surviving female children. This is more pronounced in the case of families with mothers who are younger and, even more, if they are educated.

While gender bias in mortality is shown to exist, it is less obvious when we compare the anthropometric outcomes of surviving girls and boys. On the one hand, Sen and Sengupta (1983) provide a descriptive account of malnutrition among children less than 5 years of age in two villages of the Birbhum district of West Bengal in India. The sex bias is reflected both in "(i) the greater prevalence of undernourishment of various degrees among girls than among boys (ii) in the lower growth dynamics of girls vis-a-vis boys. They also found that the village with the better over-all nutritional record has much sharper sex discrimination". On the other hand, Ryan et al. (1984) found no significant variation in anthropometric indices using data on six ICRISAT villages of Maharashtra and Andhra Pradesh in India.

Thinking about high mortality and poor anthropometric outcomes among girls in infancy and early childhood, the key suspects would seem to be less food or nutrient intake and/ or less medical care. In some earlier studies, authors found gender bias against girls in nutrition intake like Ryan et al. (1984) for south- west India. Similarly, Das Gupta (1987) found that for children aged 0-2 years in India, "boys receive food that is superior nutritionally and more valued socially". She also found higher expenditures on clothing for boys as compared to girls, shedding some light on the difference in care between boys and girls. A novel approach was developed by Subramanian and Deaton (1990) who used data on Maharashtra and estimated the expenditure elasticity of different food groups on the household budget. They were not able to find any gender differential in the intra-household allocation of food consumption. Subramanian (1995) repeated this exercise for three other Indian states with skewed sex ratios (Rajasthan, Punjab and Haryana) and found no evidence of gender bias in food consumption. Deolalikar and Rose (1998) use ICRISAT data and find increases in consumption of medicines, edible oils and fats after the birth of a male child (relative to female child) which are consistent with the preference explanation: "boys consume higher quality foods and are more likely to receive health care than girls, resulting in better health and increased survival probabilities for boys relative to girls than would exist if allocations were identical".

Pitt et al. (1990) used the 1981-82 Nutrition Survey of Rural Bangladesh and incorporate controls for activity level and body weight in the data analysis and do not find gender bias in nutrient consumption. Thus, taking into account health endowments and productivity along with the activities undertaken by Bangladeshi women, accounts for part of the differences in the average consumption of nutrients.

Results on healthcare and medical care also diverge. Subramanian and Deaton (1990) found no gender bias for medical expenses in Maharashtra, India. On the other hand, Deolalikar and Rose (1998) found higher expenditure on medicines and healthcare for male Indian children. Das Gupta (1987) also found much sharper sex differentials in medical care than in food allocation. The expenditure on medical care for sons was found to be 2.34 times higher than that for daughters in Punjab, India.

In summary, the literature on gender bias in South Asia has explored several questions in the past. There exists a plethora of descriptive evidence on skewed sex ratios and excess female mortality in this region. However among the girls who manage to survive, results on food allocation, anthropometric outcomes and medical care seem to diverge. A part of the divergent results could be attributed to the specificities of the data used and the particular regions in which these studies are conducted.

An important characteristic of developing countries is the exposure of its people to various kinds of risks and volatilities in incomes both within a given year and from year to year. One of the important sources of income volatility stems from poor rainfall, due to the dependence of a large proportion of population on agriculture and related activities. There do exist some local market and non-market mechanisms to smooth the impact of shocks across time and states of nature. But shocks are still hard to insure because of the commonality of shocks to all in a given region. The literature points that households can partially, but not completely smooth consumption (Besley, 1995).

Past research has explored the links between shocks that affect child health at time period t (like weather shocks, recessions etc.) and health states measured subsequently at period t+1. For example, Rose (1999) examines the connection between gender bias in mortality and shocks. She uses rainfall shock data for Indian districts and links it to the mortality at the district level, checking for consumption smoothing at the time of shock: a favourable rainfall shock increases the likelihood for a girl-relative to that of a boy- that she survives until school age. Similarly, using DHS data, Bhalotra (2010) analyzes the impact of GDP deviations from trend across states on infant mortality. By comparing children born to the same mother (for example, one born in recession and the other not), she is able to identify the impact of recession on the risk of death. She finds that recessions are associated with an increase in infant mortality and that these effects are heterogenous by gender. Finally, using ICRISAT data in India, Behrman (1988) found that during the lean season, parents weigh a given health-related outcome for boys almost 5 percent more heavily than the identical health-related outcome for girls. This result suggests that when faced with lean season, parents exhibit male preference.

One can also draw from other similar studies in Africa. For example, Jensen (2000) uses data from the Cote d'Ivoire and examines whether children living in areas which experience adverse climatic shocks, had lower investments in education and health. He compares the differences in height for weight Z score, children enrolled in school and the use of medical services in regions which had an adverse shock as compared to regions which experienced normal rainfall. He found an increase in the percentage of boys and girls who were malnourished and a decline in enrolment for children in shock regions. No girl-boy differences were found. Hoddinott and Kinsey (2001) examine the impact of drought (in 1995) on the growth in the heights of very young children; those aged 12 to 24 months. They use a panel data set in Zimbabwe and are thus able to measure the growth of children over time as opposed to estimating a level equation. They found that the 'drought cohort' or children aged 12 -24 months in 1995 grew, on an average, about 2 cm more slowly than other children, when measured 12 months later.

It is important to examine the effect of shocks in infancy as the consequences of underinvestment in female children during drought/ rainfall shock are likely to be high if such faltering has permanent effects. "Children that experience slow height growth are found to perform less well in school, score poorly on tests of cognitive function, have poorer psychomotor development and fine motor skills" (Dercon and Hoddinott, 2003). Indeed Maccini and Yang (2009) find that higher deviation (of early-life rainfall from the mean rainfall in one's district) has positive effects on the adult outcomes of women, but not of men in Indonesia.

3 CONCEPTUAL FRAMEWORK

In this paper, we are interested in estimating the impact of rainfall shock (R) in early childhood for all years up to point t, on health status (H) as measured at time t.

$$H_t = h(R_0, R_1, .., R_t) \tag{1}$$

Of course, we would like to understand the mechanisms through which rainfall affects child health. Thus to go beyond the reduced form relationship as described in Equation (1), we need to understand the inputs in the health demand function that can be affected by rainfall shocks. Below is a discussion outlining the relevant inputs.

Following Grossman (1972), health status at time t is a function of a vector of inputs: nutrient intake (including breastfeeding) until point t ($N_0, N_1..$), consumption of health related goods up until point t ($C_0, C_1..$), time inputs to health ($T_0, T_1..$) at each time before t, individual, parental and household endowments (K_0), demographic variables such as gender and age of the child and the individual making decisions about health (X), the availability of infrastructure in the village/ community ($V_0, V_1..$) and the disease environment such as availability of sanitation and clean water ($D_0, D_1, ..$).

$$H_t = h(N_0, N_1, .., N_t, C_0, C_1, ..C_t, T_0, T_1, .., T_t, K_0, X, V_0, V_1, .., V_t, D_0, D_1, .., D_t) \tag{2}$$

Nutrient intake (including breastfeeding), consumption of other goods (clothing, medicines, vaccinations, hygiene products etc.) and time inputs to health are assumed to have a positive impact on child health but this positive impact is decreasing (thus the production function of health is concave against each of these three inputs). There are many health benefits associated with higher/ better quality nutrient (Blau, 1984) and breastfeeding as recognized by previous studies including improved cognitive development (Kramer et al., 2008) and reduced risk of obesity (Kramer, 2010).

Regarding time inputs to health (T), health-promoting activities like "antenatal check-ups for pregnant women or preventive health care visits for children, breastfeeding, cooking healthy meals, or collecting clean water all take time to carry out" (Ferreira and Schady, 2009). These activities also have direct bearing on health.

While the aforementioned variables are necessarily choice variables of the household, endowments are not. There is indeed a well defined relationship between child growth and maternal height as postulated by Hoddinott and Kinsey (2001). Next, we move to demographic variables such as the age and gender of the individual making decisions about child health. Education of this individual may affect child health through better knowledge about health practices and inputs (e.g. knowledge about oral rehydration). For example, there are several studies which have found a positive effect of mother's education on her child's health (Aslam and Kingdon, 2012; Christiaensen and Alderman, 2004; Wolfe and Behrman, 1987). Finally, public expenditure in the provision of healthcare and health related infrastructure are important determinants of child health (Desai and Alva, 1998; Thomas et al., 1992). Disease environment determined by parent's knowledge about health promoting behaviour, availability of clean water and sanitation are important too.

Let us now discuss the inputs of the health demand function that can be affected by rainfall shocks.

It can be argued that nutrient intake along with the consumption of health promoting goods is a subset of the overall consumption by the household which in turn is a function of household income. Household income in turn depends on rainfall, especially in rural India where agriculture is major source of employment. Indeed, research has shown that there is a relationship between negative shocks and household consumption expenditures by the way of the income channel. For example, Bhalotra (2010) finds that recessions are associated with a decline in household consumption in India. Similarly, Stillman and Thomas (2008) analyzes the impact of a 2 year economic contraction in Russia in late 1990s on household consumption expenditures of food. This contraction was significant in that it led to a decline in GDP by almost one-third. They find that caloric intake was more or less unaffected by the contraction however households switched to less costly sources of calories. Regarding the consumption of health promoting goods, Paxson and Schady (2005) show that the Peruvian crisis in the late 1980s is associated with a lower health care utilization, including a higher ratio of women giving birth at home and lesser antenatal check ups. Bhalotra (2010) also finds that mothers engaged in agriculture seek less of both antenatal and post-natal health promoting activities during recessions in India. Similarly, Jensen (2000) reports that children in drought affected areas in Cote d'Ivoire are less likely to use medical care services.

Second, there is very little research that has looked at the impact of shocks on time use of parents. A study by Bhalotra (2010) finds that recessions are associated with an increase in maternal labor supply in rural India. She also finds a negative correlation between maternal labor supply and child health outcomes. She goes on to conclude that mother's time in child care is indeed an important determinant of child health. Following her argument, we can thus expect that in the event of a negative rainfall shock, if a mother decides to take on market work, then child health suffers due to less time spent by mother in child care. However, if the mother decides to work in the market because she is no longer needed on the farm (due to a negative rainfall shock), then in fact it does not necessarily mean that she spends less time in childcare. The effect of mother's time in childcare will ultimately depend on whether she is merely substituting farm work (no effect on time spent in childcare) or taking up additional work (negative effect on time spent in childcare). Even if she is taking up additional market work, she could entrust childcare to another member of the household such as an older sibling. Finally, if the mother is unable to find market work outside the farm, then a negative rainfall shock could imply more time spent in childcare and hence better child health status. In effect, rainfall's impact on the time spent by parents in childcare is ambiguous at best, but worth exploration.

In the discussion above, we argued that rainfall has an effect on income of agricultural rural Indian households (we would also show the association between rainfall and agricultural yield in India in Section 6 to provide further credence to this argument) as well time use of parents. Lastly, rainfall could alter the disease environment through the spread of water borne diseases such as malaria.

At the same time, rainfall should not have any impact on non-choice variables in theory. This is not to say that non-choice variables like demographic variables (or endowment and public expenditure) would not play out in the event of a rainfall shock. Of course variables like the education of the household head would be important in determining how the household responds to the shock. Public expenditure in the provision of healthcare can also plausibly be affected by shocks if they are 'sizeable' in magnitude and affect the potential for state governments to invest in health care provision. For example, the Peruvian crisis of the late 1980s induced the government to cut public health expenditures by half and may explain to some extent the spike in infant mortality (Paxson and Schady, 2005). We argue that with the exception of severe droughts, rainfall shocks are largely local and should not have any effect on public health expenditures. This is also a necessary condition for us as we are interested in estimating the impact of constraints at the household level on child health, and not the impact of a decline in public health expenditures, on child health.

Thus, we can write that consumption (C), nutrient intake (N), time spent in childcare (T) and the disease environment (D) are all a function of rainfall, among other factors.

$$C = c(R, A) \tag{3}$$

$$N = n(R, B) \tag{4}$$

$$T = t(R, F) \tag{5}$$

$$D = d(R, E) \tag{6}$$

We do not observe the choice variables in the health demand function (with some exceptions like vaccinations). If rainfall is exogenous, then dropping the choice variables should not have any effect on the estimates of rainfall on child health. Even if were to observe these variables and include them as control variables in our regressions, we would run into many estimation problems (for example the exogeneity of breastfeeding).

Thus, the rainfall variable captures the reduced form effect of choice variables (income, time use and disease environment) on child health. We explore these channels separately at a later stage. The relationship that we estimate is the following:

$$H_t = h(R_0, R_1, .., R_t, C_0, C_1, ..C_t, K_0, X, V_0, V_1, .., V_t, D_0, D_1, .., D_t) \tag{7}$$

In words, health is argued to be a function of rainfall in the period until time t $(R_0, R_1, ..)$ along with consumption of health promoting goods (vaccinations) and non-choice variables (endowments, demographic variables and community infrastructure).

Of course the two channels of income and time spent in childcare are interrelated. On the one hand, negative rainfall could lead to a decline in income and consequently consumption leading to worse child health outcomes. At the same time, parents may partly be able to smooth consumption by increasing the time spent working in the market. If, however, they are not able to find market work then this freed up time could imply more time in childcare and hence better child health status. To give an example, a negative rainfall shock might induce parents to not get their children vaccinated (assuming vaccines are not free) but at the same time, they may have more time to take their children to the health clinic for vaccinations.

In this paper, as a first step, we estimate the reduced form impact of rainfall on children's anthropometric outcomes using Demographic and Health Surveys for India 1998-99. We control for various determinants of health demand function as discussed in Equation (7). As a next step, we explore the mechanisms through which rainfall affects child health. We use district- level crop yield data (from the World Bank Agriculture and Climate Data) and check the impact of district level rainfall shocks on agricultural yields for Indian crops. Next, we go on to check the association between rainfall and time spent in market work by women (using Rural Economic and Demographic Survey 1998-99).

We also directly check for relationships between rainfall and different childcare activities like breastfeeding and vaccinations. One of the most important parental investment in childcare that could respond to changes in rainfall is breastfeeding. Indeed, some studies in developed countries point that the most prominent reasons for breast milk weaning seem to be mother's return to work (Baker and Milligan, 2008; Roe et al., 1999). However, literature capturing the impact of mother's labor demand on time spent by her in breastfeeding is largely limited for developing countries. In response to a positive rainfall shock, a woman might be more likely to wean the child from breastfeeding, however, it must be recognized that mothers could resort to partial breastfeeding as a result of working on the farm. In addition, Jayachandran and Kuziemko (2011) finds that girls are breastfed for a shorter duration than boys in India. Finally, the sex of the older sibling has a bearing on the duration of breastfeeding.

4 BACKGROUND AND DATA

4.1 Rainfall and Agriculture in India

The monsoon in India plays a major role in determining the harvest of major Indian crops. The agricultural season in India is divided into two prominent seasons- Kharif and Rabi (henceforth wet and dry respectively). During the wet season, the sowing of crops is undertaken at the beginning of the south-west monsoon (May- July depending on the location in India). The harvesting activities are undertaken at the end of the south-west monsoon (September to October). During the dry season, the sowing of crops is undertaken at between October to December (a relatively cooler time of the year) and the harvesting activities are undertaken between February and April. Figure 5 in the appendix provides trends of production in wet and dry season for India. Not only the wet crops have higher production in million tonnes but they also occupy more land in India.

4.2 Rainfall Data

In the absence of publicly available station rainfall data for India, we use a gridded rainfall dataset called 'Terrestrial Precipitation: 1900-2008 Gridded Monthly Time Series (Version 2.01)' interpolated and documented by Kenji Matsuura and Cort J. Willmott (with support from IGES and NASA) [1] This published dataset consists of interpolated (on a 0.5 degree latitude-longitude grid) global monthly rainfall data, from 1901 to 2008. We use Mapinfo software to merge rainfall data from 1122 weather stations spread throughout India to calculate monthly level rainfall for Indian districts.

Using the latitude and longitude information, we assigned weather stations to each of the 411 districts in DHS data (for the DHS subsample that we use for this analysis- more details in the next section). The idea was to assign to each district, weather stations in the 50 mile radius from the centroid of the district. Thereafter, we used the Inverse Distance Weighting (please refer to subsection 9.1 of the appendix for more on this) to interpolate monthly rainfall values for 411 districts.

[1] The dataset is provided by Center for Climatic Research, Department of Geography, University of Delaware. Terrestrial Precipitation: 1900-2008 Gridded Monthly Time Series - Version 2.01, interpolated and documented by Kenji Matsuura and Cort J. Willmott (with support from IGES and NASA). For further information about this dataset, please refer to Legates and Willmott (1990) as the source for rainfall data.

For regression analysis, we consider rainfall data corresponding to children in the age group of 13- 36 months at the time of the survey. We identify the months from May- October as the wet season and consequently November- April as the dry season as these should be most closely related to agricultural cycles. So if a child is born in August 1994, the first wet season for the child would be May to October 1994 and the first dry season would be November 1994 to April 1995. The principal measure of rainfall that we use is defined below (we use other measures too for robustness checks, please refer to subsection 9.2 in the appendix).

The measure of rainfall that we use based is on percentiles and has been used previously for India. [2] The variable equals 1 if rainfall in wet season around birth is above the 20th percentile (positive shock) for the district, and 0 if it is below the 20th percentile (negative shock). We use rainfall in the wet seasons between 1971 and 2004 (44 years) to calculate percentiles. Similarly we construct variables for rainfall experienced in utero, second year after birth, third year after birth. We also used other measures of rainfall shock (refer to appendix for details).

4.3 Health Data

The data for the analysis of health outcomes among children comes from the second round of Demographic and Health Surveys conducted in 1998-99.[3] DHS is a nationally representative household survey and provides data for a wide range of issues pertaining to in health, nutrition and demographics. The survey was administered nationwide to ever married females aged 15-49 years. The rural sample in each state, which we use in the study was selected as follows: within each state, primary sampling units (PSUs) were selected using a probability proportional to the population. Thereafter, within each PSU, households were randomly selected.

We observe the height and weight for children in the age group of 0-36 months at the time of the interview, born to mothers in the age group of 15-49 years. However we restrict this analysis to children aged 13-36 months as the impact of rainfall in the years around birth is likely to show up on children aged 1 and older. Another reason is the concern raised about the accuracy of measuring height and weight for children less than 1 year of age.

The outcomes that we are interested in are height for age Z scores (HAZ) and weight for age Z scores (WAZ). HAZ and WAZ are expressed as standard deviations from US National Center for Health Statistics (NCHS) standard of mean, used by the World Health Organisation (WHO),

[2] See Jayachandran (2006)

[3] We do not use the first round of DHS because there are a lot of missing observations for height and weight.

standardized by gender and age. While weight is a measure of short-term health status, height on the other hand is a stock variable and can be considered to be a long term predictor of nutrition. All eligible children had their height and weight measured, with some exceptions (refer to Table A-1 in appendix to see the details of the sample used for analysis). Out of the total 27250 children, anthropometric data was measured for 24855 children out of which 18044 live in rural areas. After accounting for missing observations and restricting this sample to children only above 12 months of age, the final sample comprises of 5104 girls and 5556 boys.

As a first step, we estimate the reduced form impact of rainfall on children's anthropometric outcomes. In examining the impact of birth year rainfall on HAZ and WAZ of children, we do not have access to nutrient intake of children. We could control for the duration of breastfeeding however it is likely to be endogenous as mothers are likely to breastfeed children who have poor health. However, we include characteristics like wealth of the household and also include a dummy for whether the child has had any vaccination.

Further, we control for individual characteristics such as birth order of the child, preceding birth interval and season of birth. We also include the number of sisters and brothers under 13 years of age, born to the mother and to other adult women in the household to control for composition effects. In a separate specification, we include month of birth fixed effects to account for fertility decisions.

We do not have time -use data in the DHS, however we control for dummies of father's occupation, whether the mother works on farm, distance to health centre and presence of traditional attendant in village. Finally, we have included directly for height and weight for the mother of the children thus accounting for genetic endowment. It is likely that taller and thinner mothers would have taller and thinner children respectively, all else being same. For example, Hoddinott and Kinsey (2001) find a well defined relationship between child growth and maternal height. As far as the demographic variables are concerned, we use various parental and household level characteristics. Household characteristics include an index of wealth, sex and age of household head and dummies for caste and religion. Parental characteristics include variables such as the number of years of completed schooling of the mother and father, the age and the square of age of mother. The age of the mother has an ambiguous effect on the child's health: older mothers might be expected to have more children thus putting a strain on the amount of time that is dedicated to the well being of each child. However, it might be that older mothers have extensive experience in childcare which might make them more knowledgeable about child health practices.

Finally, we include various village infrastructure variables which include distance from the nearest all weather road, whether the village is electrified, population of the village, presence of a traditional attendant in the village, distance to all weather road, to health sub centre and to community health centre. The disease environment in part is captured by the rainfall shock variables.

Table 1 provides descriptive statistics on anthropometric outcomes and explanatory variables used in our analysis. The anthropometric outcomes that we are interested in are height for age Z score (HAZ) and weight for age Z score (WAZ) for children in the ages of 13 to 36 months. The value of these variables lies between -6 and 6. The height for age Z score for children averages around -2.5 for girls and boys whereas the weight for age Z score averages around -1.9 for both groups. The children whose height (weight) for age Z score is between -2.0 and -2.99 standard deviations (SD) below the mean on the WHO international references standard are classified as moderately stunted (underweight). This sheds some light on the general status of the underperformance on anthropometric outcomes in the country. At the same time, in line with other studies, there does not seem to be any gender bias in anthropometric outcomes.

It is worthwhile to note that about 80 percent of boys and girls experienced positive rainfall in the first wet season around birth. The duration of breastfeeding (which includes children still being breastfed) is 19.26 months for boys and 18.58 months for girls, observed to be about 3/4 of a month higher for boys and significant. The World Health Organization (2003, pp. 7-8) recommends that infants should be exclusively breastfed throughout the first six months of their life. It also recommends that mothers continue to breastfeed children after 6 months upto two years or more even while other foods are being introduced into their diet. It seems that women continue to breastfeed children for a long time in India.

A smaller percentage of girls aged 13-36 months have vaccination as compared to boys of the same age. This is in line with evidence from Jayachandran (2006). About 80% of children have received any vaccination in our sample. The birth order of the children in the sample averages around 2.9 for girls and boys. Regarding household characteristics, the household head is a male in 94 percent of the households with an average age around 43.82 for girls and 43.46 for boys. The wealth score calculated using principal component analysis indicates that girls belong to less wealthier households than boys. Mother's height and weight averages around 151.65 cm and

44.7 kg respectively. The average age of the mother is 25.77 for girls and 25.89 for boys. The father and mother of boy households tend to be more educated that girl's parents. The fathers also tend to be more educated than the mothers. There are no significant differences for girls and boys, on an average, on village and community characteristics.

5 EMPIRICAL STRATEGY

In examining the relationship between early life rainfall and subsequent health outcomes for children, we use child's height for age Z score and weight for age Z scores at the time of the interview. We restrict the sample to all eligible children in rural areas as the effect of the lack/ abundance of rainfall is likely to be highest here. We run all the regressions separately for boys and girls.

We estimate the relationship between rainfall shock and health outcome for each gender as follows:

$$Y_{ihrt} = \beta_0 + \beta_1 * R_{rt} + \beta_2 * X_{ihrt} + \beta_3 * A_{hrt} + \beta_4 * C + \delta_r + \beta_5 \eta + \mu_{ihrt}$$

Where Y_{ihrt} is the health outcome for child 'i' in household 'h' in district 'r' born in cohort 't'. R_{rt} is an indicator of rainfall shock in district 'r' in cohort/year 't'. X_{ihrt} is a vector of control variables at the level of the child. A_{hrt} is vector of household level and maternal control variables which might have a direct bearing on child's health outcomes. C captures indicators at the village level. District fixed effects (δ_r) capture time invariant features of districts, including determinants of quality of care that do not change over time and accounts for unobserved heterogeneity across districts. We also have season of birth fixed effects captured by η. The individual specific standard error term is given by μ_{ihrt}. Standard errors are clustered at the district level. Clustering standard errors at the level of the DHS district allows for an arbitrary variance covariance structure within birth districts to account for possible correlation of errors within the same sampling cluster. Finally and to be sure, we identify the impact using the exogenous change in rainfall in a district over time thus comparing children born in different years (and so experiencing different rainfall) but in the same district and season. For robustness checks, we also include rainfall variables for period 't-1' (in utero) and 2-4 years after birth. Rainfall measures in the third and fourth year after birth should not have a significant impact on child health as the child has not experienced them yet.

One must recognize the role of selective mortality in India. Rose (1999) examined the connection between gender bias in mortality and shocks for India. She uses rainfall shock data at the district level and links to the mortality among girls, checking for consumption smoothing at the time of shock: a favourable rainfall shock increases the likelihood relative to that of a boy that a girl survives until school age. In such a case, one can argue that the weaker girls have already died and we are left with a healthier sample of girls thus introducing selection. To employ a selection model, it would be imperative to justify the exclusion restriction of the instrument used. However, it is almost hardly possible to find a factor that affects the probability of a neonatal death without having an impact on height and weight. Thus, it would be worthwhile to mention that our impacts of rainfall on nutritional outcomes are lower bound estimates of the real causal estimates.

6 RESULTS

6.1 Anthropometric outcomes

The measure of rainfall that we use in Table 2 is a rainfall shock variable in percentiles explained in subsection 4.2. Taking negative rainfall as the base (rainfall in the lowest 20 percentile), children born in areas which received positive rainfall in the first wet season after birth have better outcomes. The magnitudes are large and significant, although slightly larger for girls as compared to boys. The placebo test is the inclusion of rainfall in other years after birth- they do not seem to have an effect on child health (as demonstrated in Table 2 as well as Figure 3 and Figure 4). Thus, it is clear that the effect of rainfall manifests itself in utero and the first year after birth only. Next we introduce month of birth fixed effects to the specification, to account for the choice of parents to have children at a particular month/ season in the year (results not shown). Results for first year wet season rainfall remain the same. We also check for robustness of these results using different measures of rainfall shocks (results reported in table A-3 in Appendix, refer to subsection 9.2 in appendix for more details on the construction of these variables). Overall, it is clear that positive rainfall shocks have a significant improving effect on HAZ and WAZ of both girls and boys.

For detailed results, refer to table A-4 in appendix. Some interesting findings emerge. The higher the number of sisters, the lower is the HAZ of girls. This is in line with much of the literature on India which suggests that girls tend to have more siblings on an average as compared to boys, thus fewer resources allocated to every child. Children living in wealthier households and born to more educated mothers have better outcomes, irrespective of gender. Girls born to more educated fathers also tend to have better outcomes but the same is not observed for boys. As expected, mother's height and weight is significant for all outcomes and across both genders. Interestingly, girls born in households where the household head is male have better HAZ as well. Age of the mother is seen to have no effect on outcomes. Finally, it is found that girls have lower HAZ if they are from Muslim households and boys have better WAZ if they are from the General caste (upper caste).

In table 2, we have run regressions separately for girls and boys. Thus, currently, we are comparing girls who experienced low rainfall around birth with girls who received good rainfall around birth, and similarly for boys. However, it would be interesting to see if negative rainfall deviation affects girls more than boys. To capture this effect, we introduce an interaction between gender and the rainfall variable and find (in Table 3) the interaction variables to be not statistically significant. Thus, from these results, it is not clearly evident that girls bear a disproportionate burden from negative rainfall shocks.

6.2 Exploring the mechanisms

As discussed in the conceptual framework, in addition to the disease environment, there are two potential channels through which rainfall could affect child health. Negative rainfall shocks have a negative effect on income (through its impact on agricultural output), and and ambiguous impact on the relative price of parent's time. We have found that negative rainfall shocks negatively affect children's health outcomes. Let us now turn to each of the mechanisms.

In order to establish the link from rainfall to income to consumption to health, we would ideally like to have information on consumption or income of households. In the DHS, this information is not readily available. Thus, we resort to testing the effect of rainfall shocks on the crop yields (data on crop yields sourced from the World Bank Agriculture and Climate Data). This dataset contains crop yields of all major Indian crops at the district level from 1951 to 1987[4]. We test the impact of rainfall shock in each year and in the wet season on the yield of wheat, rice, bajra, jowar and maize of that particular year, controlling for various agricultural inputs (such as fertilizers, labor, bullocks and machines), population density and literacy of males in the district. The results are provided in Table 4. We see that rainfall in the lowest quintile is

[4] We include only 1956 to 1987 in our analysis as the data for 1951 to 1955 contains a lot of missing data

associated with reduced yields for all 5 major Indian crops. Thus rainfall shocks represent a clear income shock for rural India.

Some of negative effect of negative rainfall shocks can be smoothed by taking up market work. Thus parents might respond to more or less rainfall by increasing or decreasing time spent in the non-agricultural sector. However lesser labor demand on parents during lean season could also mean more time spent in domestic chores including childcare. In order to test this hypothesis, we use time-use data of adult women reported in the 1998-99 round of REDS survey conducted by National Council of Applied Economic Research, Delhi[5]. The questionnaire asked about time use for three time periods in the year 1998-99 (October/ November 1998, February 1999 and April/ May 1999). We restrict ourselves to women in the age group of 15-30 years old (see Table A-2 in the Appendix for more details on the sample used for analysis). Table 5 shows the descriptive statistics of time use in various activities for this group of women in 3 different time periods in the year. The period of October/ November is the key season for harvesting of wet season crops. It is clear that women spend slightly more time in agricultural activities and less time in market work in October/ November. With respect to household work of which childcare is a part, there does not seem to be any significant difference across seasons.

Let us now turn to checking the impact of rainfall on these various activities. We check the impact of rainfall in the wet season of 1998 on time use of women in October/ November 1998, after controlling for state fixed effects. Thus, we are comparing time use of women who experienced different rainfall in the wet season of 1998 within each state. Results are presented in Table 6 for October/ November period. Using the measure of rainfall based on percentiles, we do not find any impact of rainfall shocks on time spent in agriculture and related activities or market work (here market work comprises of non-agricultural wage work, non-agricultural self employed work and salaried work). However, using the continuous measure of rainfall (refer to subsection 9.2 in appendix for more details on this measure), we do find evidence of more time spent on market activities and less time spent in agricultural activities when the rainfall is less in wet season. We

[5]We use the 1998-1999 round of the REDS panel survey conducted by National Council of Applied Economic Research, Delhi in 1971, 1982 and 1999. The first round of REDS was conducted in 1971 and included complete village and household information from 4,527 households spread over 259 villages from 17 major states of India. The 1971 sample was designed to be representative of rural areas in India. The 1981-1982 round excluded Assam because of an insurgency at the time, but is claimed to be nationally representative of rural areas. It surveyed a total of 4,979 households across 250 villages. Finally, the 1998-99 survey covered all surviving 1982 households (except for those in Jammu and Kashmir due to unrest there) and added a small random sample of new households from the villages interviewed in previous rounds to make the sample representative. Together with household division since 1982, this results in a sample of 7,474 households; a village-level survey also accompanied the household survey.

do not find any effect of rainfall on time spent in domestic work.

One must recognize that using two different datasets to understand the effect of rainfall shocks on anthropometric outcomes and time use poses problems. If the samples in the two datasets represent different segments of the population, then we may run into making misleading conclusions. Thus in Table A-5, I compare the key characteristics of rural households where women aged 15-30 were interviewed in the two surveys- REDS and DHS in 1998-99 (this is because the sample of REDS is restricted to these women). As far as household size and sex of the household head is concerned, the two surveys do not have any significant differences. There are slightly more number of Hindu households in the REDS surveys and the age of the household head is 2 years more in the REDS survey. Our conclusions regarding the results on time use and anthropometric outcomes may thus arguably be comparable. In any case, to further substantiate whether negative shocks affect time spent in childcare, we check the impact of rainfall shocks directly on some child care activities like breastfeeding and vaccinations.

In DHS 1998-99 data, we have in children for whom breastfeeding has finished and for whom it is still ongoing. Since the data is censored, we use Cox's proportional hazard model as this technique adjusts for truncation bias by incorporating both complete and incomplete segments of histories in the analysis of breastfeeding-related data[6].

We now describe the set up of the data and the assumptions we make. We know for each child in the age group of 0 to 36 months- the number of months the child has been breastfed and whether or not the child is being breastfed at the time of the survey. We restrict our sample to children for whom breastfeeding stopped in the wet season as rainfall is most likely to affect the choice of the mother regarding breastfeeding their children in this period. We build a censor variable equal to 1 if the event has occurred (breastfeeding had stopped for the child as reported in the survey), and 0 otherwise. We then reconstruct the data to have one observation per child per month. Our outcome variable is continuous- the number of months that the child was exposed to the event (stoppage of breastfeeding). We assume that only one of the covariates is time-varying, the rainfall shock variable (even though other covariates are also time-varying like distance to an all weather road, however we only have information about those variables at the time of the survey).

The rainfall shock variable is built as follows: For children 0-12 months old- it is equal to 1 if

[6] Please refer to subsection 9.3 in the Appendix for more details on the Cox's proportional hazard model.

rainfall experienced in the first wet season around birth is in the lowest 20 percentile and 0 zero otherwise. For children 13-24 months old- it is equal to 1 if rainfall experienced in the second wet season around birth is in the lowest 20 percentile and 0 zero otherwise. For children 25-36 months old- it is equal to 1 if rainfall experienced in the third wet season around birth is in the lowest 20 percentile and 0 zero otherwise.

To give an example, imagine a 28 month old girl at the time of the survey for whom breastfeeding has not stopped yet. For this child, there are 28 observations in the data corresponding to each month that she was exposed to the risk of termination of breastfeeding. The censor variable is 0 for each of the 28 observations. The rainfall variable varies: this girl has experienced three wet seasons. For the observations under 12 months of age, she is assigned the rainfall variables corresponding to the first wet season around/ after birth. For observations between 13 and 24 months, she is assigned rainfall variable corresponding to the second wet season around/ after birth. For observations between 25 and 28 months, she is assigned rainfall variable corresponding to the third wet season around/ after birth. This is done to ensure that the rainfall variable captures the effect of positive or negative shock in the year that the breastfeeding stopped, on the outcome variable.

For the question at hand, the hazard function measures the risk of stoppage of being breastfed at time 't', given that the child has been breastfed until time 't' and a set of characteristics X. Based on this hazard function, a log partial likelihood function is maximized to produce maximum partial likelihood estimates of the model parameters. In our case, the model we estimate gives the impact of rainfall shock on risk of termination of breastfeeding for children aged 0-36 months in rural India.

Table 7 shows the estimates of the impact of rainfall shock on the hazard of stoppage of breastfeeding. Columns 1 and 2 show the coefficients for girls and boys separately. We do not find that stoppage of breastfeeding responds to positive shocks. Thus we cannot draw any meaningful conclusion from this analysis. We do find though that high birth order children have a lower risk of stoppage of breastfeeding.

In all the regressions with anthropometric status as outcome variables, we included a dummy for vaccination as an explanatory variable. In addition, we check whether bad rainfall at the age at which the child is supposed to receive different vaccinations (following the vaccination schedule of the Indian Academy of Pediatrics) affects the probability of being vaccinated (results not shown). As discussed earlier, there are two ways in which rainfall could affect this outcome- either by making it more or less affordable or by the effect through parent's time use. There is no impact that we find here.

In addition to the above, we also check if rainfall affects the probability of getting medical treatment when the child has fever/ cough (result not shown). Restricting to interviews conducted in the wet season of 1998, we check if the rainfall in the wet season of 1998 affects the probability of getting medical care (in the questionnaire, it was asked if medical care was sought recently in the event of experiencing fever/ cough). Again, we do not find any association between rainfall shock in 1998 and the likelihood of getting medical attention for fever/ cough, among children who did suffer from this ailment in the wet season of 1998.

In summary, higher income associated with positive rainfall could have made health care more affordable. Even though women might spend more time in market work in lean season, we do not find any indication in these results that negative rainfall is associated with more time spent in childcare or vice-versa. Of course, even if our results pointed in the direction that mothers do spend less time in child care during good rainfall years, it could just be that an older sibling or other member of the household is spending more time in childcare instead.

6.3 Extensions

An important factor to consider is that rainfall is known to be quasi random and it could be correlated over time. If it were to be correlated then it would be difficult to isolate the impact of birth year rainfall from the in utero rainfall or other years, calling into question the identification. As mentioned before, looking at the impact of rainfall in the third and fourth year of birth of children who are 13 to 36 months old at the time of survey, we found no impact on children's health.

Further, we must consider that the impact of rainfall shock on heterogeneous groups. Table 8 looks at the effect on shocks in the 7 richest and 6 poorest Indian states. Similarly in Table 9, we check the impact of shocks based on the wealth of the household. It turns out that rainfall shocks have an impact on child health only in poorer states and poorer households. It is likely that poorer states and poorer households rely more heavily on agriculture for their income and hence rainfall shocks affecting agriculture have a larger impact on them. Finally, Table 10 summarises the results by education of mother. The results seem to point out that the impact of rainfall shock is more pronounced for girls born to uneducated mothers while no effect is found for boys. We check whether girls born in poorer states, poorer households and to uneducated mothers are more likely to be discriminated against by looking at the estimates of the interaction of gender and rainfall shock variable. Once again, we do not find any evidence of gender discrimination.

Finally rainfall could affect child health through the spread of water borne diseases like malaria. However, looking at Figure 6 in the appendix shows us the age and sex distribution of malaria mortality in India. It is observed that men are reported to have higher malaria mortality rates than women and that malaria is very less concentrated among children in India. Thus, it would be safe to rule this possibility out.

7 CONCLUSION

While there is mixed evidence of discrimination against girls in the allocation of resources under normal circumstances, evidence regarding the disproportionate allocation of resources under harder circumstances is still scarce. At the same time, it is found that the child sex ratio (0 to 6 years) has dropped below sex ratio at birth between Census of India 1981 and Census of India 2001, suggesting that more girls are dying in the ages of 0 to 6 years than boys. However it could very well be argued that even girls which manage to survive are more undernourished as compared to boys. It is under this context that we check the impact of rainfall shocks around birth on health outcomes of children aged 13 to 36 months.

There are two potential channels that we explore through which rainfall affects the health of children. First is the income effect: when households suffer a shock on their income, they may allocate resources among boys and girls differently leading to different anthropometric outcomes. Secondly, the amount of rainfall could determine the time spent by parents in childcare thus impact child's health.

Of course the two channels of income and time spent in childcare are interrelated. On the one hand, negative rainfall could lead to a decline in income and consequently consumption leading to worse child health outcomes. At the same time, parents may partly be able to smooth consumption by increasing the time spent working in the market. If, however, they are not able to find market work then this freed up time could imply more time in childcare and hence better child health status.

The results reveal that children who experience positive rainfall shocks in the wet season in utero and first year after birth have better height for age Z scores and weight for age Z scores as compared to children who experienced negative rainfall shock. The results are higher in magnitude for girls as compared to boys. Further, results point in the same direction irrespective of the measure of rainfall shock used. Controlling for rainfall shock in the wet season for upto 4 years after birth, the estimates of in utero and first year rainfall stay significant. Taking the interaction between rainfall deviation and gender, we do not find that girls bear a disproportionate burden (in terms of deteriorated health) from these shocks.

Exploring the mechanisms, we find that the income effect is dominant in explaining the negative impact of negative shocks on children's health. This is further corroborated by the finding that children living in poorer states, poorer households and girls mothered by uneducated women find it harder to smooth consumption when faced with negative rainfall shocks.

These results have important policy implications. Over the past years, there has been an increased interest in weather based index insurance wherein farmers are insured against bad weather. This program has also been tested in some parts of India using experiment based surveys. Our results suggest a negative impact of bad rainfall on the height and weight for children. Since these negative effects determine the long run attainment of good health, weather based insurance programs could help to improve outcomes by providing a way to smooth consumption. Another policy response could be providing support programmes during lean periods for drought stricken areas in India.

8 BIBLIOGRAPHY

References

Aslam, M. and G. G. Kingdon (2012). Parental Education and Child Health- Understanding the Pathways of Impact in Pakistan. *World Development 40*(10), 2014–2032.

Baker, M. and K. Milligan (2008). Maternal employment, breastfeeding, and health: Evidence from maternity leave mandates. *Journal of Health Economics 27*(4), 871–887.

Basu, A. M. (1989). Is discrimination in food really necessary for explaining sex differentials in childhood mortality? *Population Studies 43*(2), pp. 193–210.

Basu, A. M. (1993). How pervasive are sex differentials in childhood nutritional levels in south asia? *Biodemography and Social Biology 40*(1-2), 25–37.

Behrman, J. R. (1988, March). Intrahousehold allocation of nutrients in rural india: Are boys favored? do parents exhibit inequality aversion? *Oxford Economic Papers 40*(1), 32–54.

Besley, T. (1995, October). Property rights and investment incentives: Theory and evidence from ghana. *Journal of Political Economy 103*(5), 903–37.

Bhalotra, S. (2010). Fatal fluctuations? cyclicality in infant mortality in india. *Journal of Development Economics 93*(1), 7–19.

Blau, D. (1984). *A Model of Child Nutrition, Fertility and Women's Time Allocation: The Case of Nicaragua.*, Volume edited by T. P. Schultz and K. Wolpin. Greenwich, Conn. JAI Press.

Christiaensen, L. and H. Alderman (2004, January). Child Malnutrition in Ethiopia: Can Maternal Knowledge Augment the Role of Income? *Economic Development and Cultural Change 52*(2), 287–312.

Das Gupta, M. (1987). Selective discrimination against female children in rural punjab, india. *Population and Development Review 13*(1), pp. 77–100.

Dash, A. (2009). *Estimation of true malaria burden in India: a profile of National Institute of Malaria Research.* National Institute of Malaria Research, New Delhi, India.

Deolalikar, A. and E. Rose (1998). Gender and savings in rural india. *Journal of Population Economics 11*(4), 453–470.

Dercon, S. and J. Hoddinott (2003). Health, shocks and poverty persistence. Working Papers UNU-WIDER Research Paper, World Institute for Development Economic Research (UNU-WIDER).

Desai, S. and S. Alva (1998, February). Maternal education and child health: Is there a strong causal relationship? *Demography 35*(1), 71–81.

Dreze, J. and A. Sen (1991, September). *Hunger and Public Action*. Number 9780198283652 in OUP Catalogue. Oxford University Press.

D'Souza, S. and L. C. Chen (1980). Sex differentials in mortality in rural bangladesh. *Population and Development Review 6*(2), pp. 257–270.

Ferreira, F. H. and N. Schady (2009). Aggregate economic shocks, child schooling, and child health. *The World Bank Research Observer 24*(2), 147–181.

Grossman, M. (1972). On the concept of health capital and the demand for health. *The Journal of Political Economy 80*(2), 223–255.

Hoddinott, J. and B. Kinsey (2001, September). Child growth in the time of drought. *Oxford Bulletin of Economics and Statistics 63*(4), 409–36.

Jayachandran, S. (2006, June). Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy 114*(3), 538–575.

Jayachandran, S. and I. Kuziemko (2011). Why do mothers breastfeed girls less than boys? evidence and implications for child health in india. *The Quarterly Journal of Economics 126*(3), 1485–1538.

Jensen, R. (2000, May). Agricultural volatility and investments in children. *American Economic Review 90*(2), 399–404.

Kramer, M. S. (2010). Breastfeeding, complementary (solid) foods, and long-term risk of obesity. *The American journal of clinical nutrition 91*(3), 500–501.

Kramer, M. S., F. Aboud, E. Mironova, I. Vanilovich, R. W. Platt, L. Matush, S. Igumnov, E. Fombonne, N. Bogdanovich, T. Ducruet, et al. (2008). Breastfeeding and child cognitive development: new evidence from a large randomized trial. *Archives of general psychiatry 65*(5), 578.

Kynch, J. and A. Sen (1983). Indian women: well-being and survival. *Cambridge Journal of Economics 7*(3-4), 363.

Legates, D. R. and C. J. Willmott (1990). Mean seasonal and spatial variability in gauge-corrected, global precipitation. *International Journal of Climatology 10*(2), 111–127.

Maccini, S. and D. Yang (2009, June). Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review 99*(3), 1006–26.

Mishra, V., S. Lahiri, and N. Y. Luther (1999). Child nutrition in india. national family health survey. Subject reports no. 14., Mumbai: International Institute for Population Sciences; and Honolulu: East-West Center.

Paxson, C. and N. Schady (2005). Child health and economic crisis in peru. *The World Bank Economic Review 19*(2), 203–223.

Pitt, M. M., M. R. Rosenzweig, and M. N. Hassan (1990). Productivity, health, and inequality in the intrahousehold distribution of food in low-income countries. *The American Economic Review 80*(5), pp. 1139–1156.

Roe, B., L. A. Whittington, S. B. Fein, and M. F. Teisl (1999). Is there competition between breast-feeding and maternal employment? *Demography 36*(2), pp. 157–171.

Rose, E. (1999). Consumption smoothing and excess female mortality in rural india. *The Review of Economics and Statistics 81*(1), pp. 41–49.

Ryan, J. G., P. D. Bidinger, N. P. Rao, and P. Pushpamma (1984). The determinants of individual diets and nutritional status in six villages of south india. Technical report, Hyderabad, India: ICRISAT-NIN-APAU.

Sen, A. (1981). *Poverty and FaminesAn Essay on Entitlement and Deprivation.* Oxford University Press.

Sen, A. (1990). More than 100 million women are missing. *The New York Review of Books 37*(20), 61–66.

Sen, A. and S. Sengupta (1983). Malnutrition of rural children and the sex bias. *Economic and Political Weekly 18*(19/21), pp. 855–857+859–861+863–864.

Sen, A. K. (1988). Family and food: sex bias in poverty.

Stillman, S. and D. Thomas (2008). Nutritional status during an economic crisis: Evidence from russia*. *The Economic Journal 118*(531), 1385–1417.

Subramanian, S. (1995). Gender discrimination in intra-household allocation in india. mimeo, Department of Economics, Cornell University.

Subramanian, S. and A. Deaton (1990). Gender effects in indian consumption patterns. Papers 147, Princeton, Woodrow Wilson School - Development Studies.

Thomas, D., V. Lavy, and J. Strauss (1992). Public Policy and Anthropometric Outcomes in Cote d'Ivoire. Papers 89, World Bank - Living Standards Measurement.

Wolfe, B. L. and J. R. Behrman (1987, September). Women's schooling and children's health : Are the effects robust with adult sibling control for the women's childhood background? *Journal of Health Economics 6*(3), 239–254.

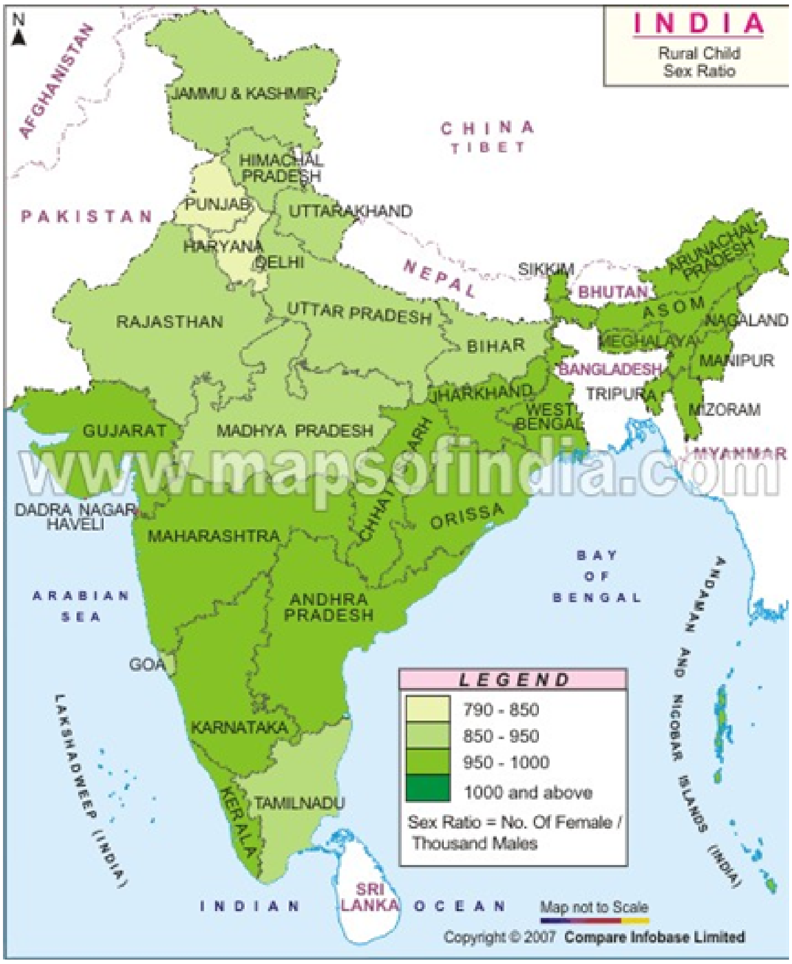


Figure 1: Rural Child Sex Ratio for Indian states, 2011

Source: `http://www.mapsofindia.com/census/rural-child-sex-ratio.html`

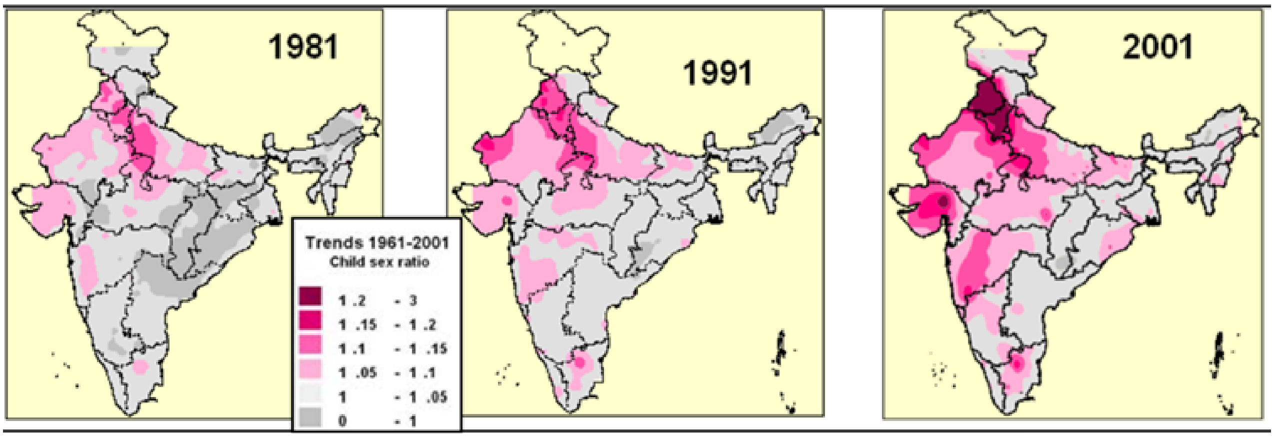


Figure 2: Evolution of child (0-4 years) sex ratio in India at the district level

Source: Characteristics of Sex-Ratio Imbalance in India, and Future Scenarios by Christophe Z Guilimoto

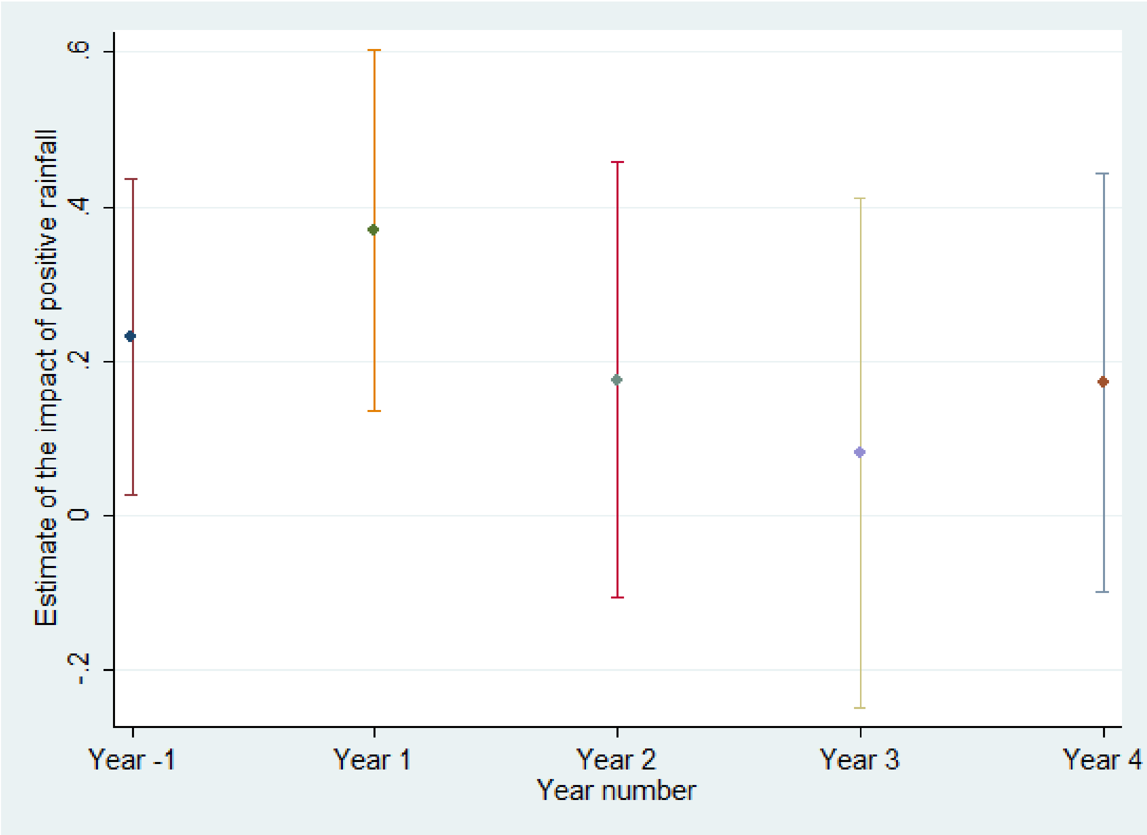


Figure 3: Estimates of the impact of rainfall shock in years around birth on HAZ of girls

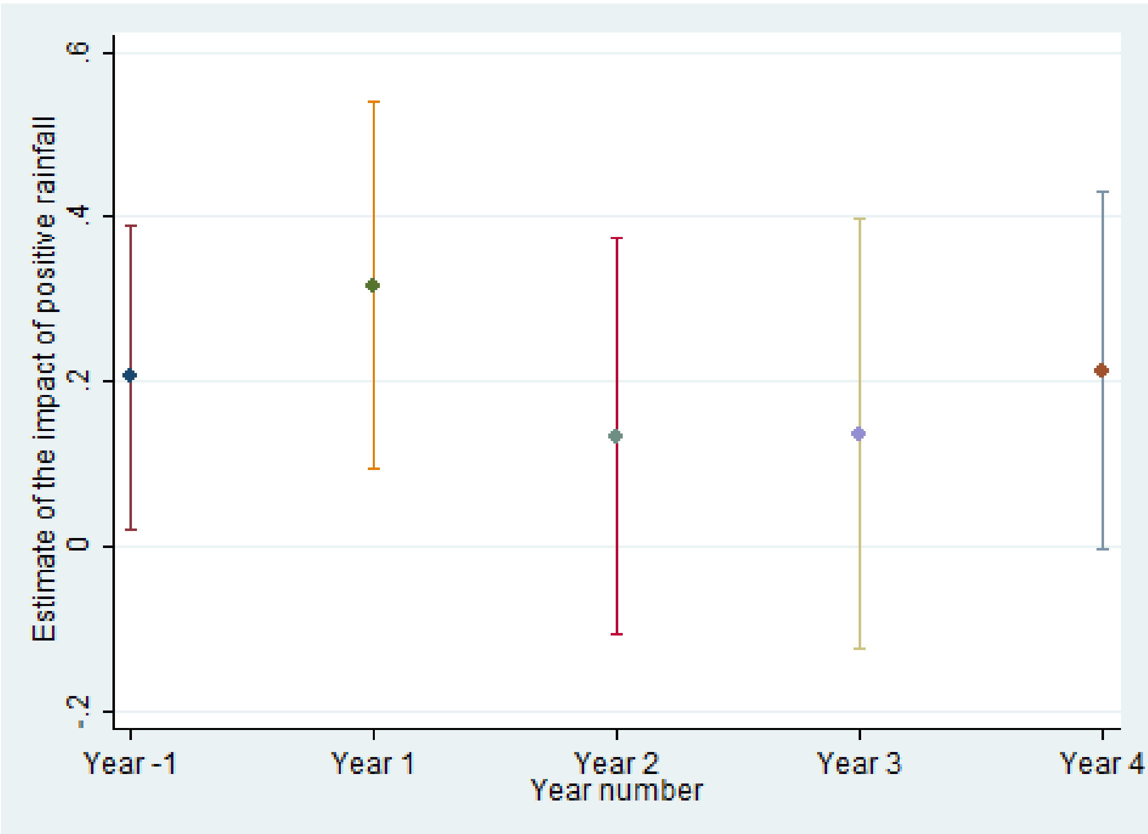


Figure 4: Estimates of the impact of rainfall shock in years around birth on HAZ of boys

Table 1: Characteristics by gender

	Girl	Boy	Difference
HAZ	-2.50	-2.52	0.02
	(1.66)	(1.64)	
WAZ	-1.92	-1.90	-0.02
	(1.33)	(1.26)	
Positive rainfall in year 1	0.80	0.81	-0.01
	(0.40)	(0.39)	
Duration of breastfeeding	18.58	19.29	-0.71***
	(7.36)	(7.66)	
Received vaccine dummy	0.84	0.86	-0.01*
	(0.36)	(0.35)	
Birth Order	2.87	2.91	-0.04
	(1.90)	(1.92)	
preceding birth interval	35.98	35.69	0.28
	(18.66)	(17.99)	
Number of brothers under 13	0.74	0.68	0.06***
	(0.85)	(0.83)	
Number of boys under 13 in HH	2.51	2.47	0.04
	(2.30)	(2.28)	
Number of sisters under 13	0.79	0.84	-0.05**
	(0.93)	(0.97)	
Number of girls under 13 in HH	2.40	2.48	-0.08
	(2.23)	(2.31)	
Sex of HH Head	0.94	0.94	-0.00
	(0.24)	(0.24)	
Age of HH Head	43.81	43.42	0.39
	(15.39)	(15.18)	
Wealth Score	-0.44	-0.39	-0.05***
	(0.71)	(0.73)	
Mother's height	151.62	151.69	-0.07
	(5.55)	(5.51)	
Mother's weight	44.74	44.72	0.01
	(6.60)	(6.57)	
Age of mother	25.77	25.89	-0.12
	(5.43)	(5.45)	
Education of mother (in years)	2.98	3.21	-0.23**
	(3.98)	(4.19)	
Education of father (in years)	5.68	5.87	-0.19*
	(4.76)	(4.86)	
Traditional attendant in village	1.42	1.43	-0.01
	(0.49)	(0.49)	
Population of village	10.49	10.41	0.08
	(5.78)	(5.86)	
Distance to all weather road	14.43	14.30	0.13
	(28.99)	(28.70)	
Distance to health sub centre	4.83	5.30	-0.47
	(12.55)	(13.66)	
Distance to community health centre	17.88	18.11	-0.23
	(21.14)	(21.00)	
Obs	5077	5515	10592

The sample used is children aged 1-3 year old children in the Demographic and Health Survey 1998-99.
Standard deviation in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 2: Impact of Rainfall Shocks on health outcomes

	(HAZ score)		(WAZ score)	
	(Girl)	(Boy)	(Girl)	(Boy)
Positive rainfall in utero	0.232**	0.205**	0.124*	0.086
	(0.105)	(0.093)	(0.074)	(0.066)
Positive rainfall in year 1	0.369***	0.317***	0.283***	0.215***
	(0.119)	(0.113)	(0.081)	(0.080)
Positive rainfall in year 2	0.176	0.133	0.092	0.069
	(0.143)	(0.122)	(0.101)	(0.081)
Positive rainfall in year 3	0.081	0.137	0.032	0.044
	(0.169)	(0.132)	(0.111)	(0.091)
Positive rainfall in year 4	0.172	0.213*	0.172*	0.129*
	(0.138)	(0.110)	(0.100)	(0.078)
Observations	5077	5515	5077	5515
R^2	0.244	0.227	0.291	0.284

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
The sample used is children aged 1-3 year old children in the Demographic and Health Survey 1998-99.
Positive rainfall is wet season rainfall greater than 20th percentile.
The regressions include season of birth and district fixed effects. Also includes controls for birth order, preceding birth interval, dummy for child received any vaccine, number of sister and brothers under 13 of the parents and in the household, age and sex of household head, wealth index quintile, age, age square, height and weight of mother, years of schooling of mother and father, dummy for mother working on farm, categorical variable for occupation of father, religion and caste. Village level control variables are village electrification, traditional attendant in village, population in village, distance to all weather road, health sub centre and community health centre.

Table 3: Impact of Rainfall Shocks on gender bias in health outcomes

	(With SOB FE)		(With MOB FE)	
	(HAZ)	(WAZ)	(HAZ)	(WAZ)
Positive rainfall in year 1	0.211**	0.152**	0.158**	0.120**
	(0.082)	(0.060)	(0.076)	(0.057)
Positive rainfall in utero	0.141*	0.094	0.071	0.054
	(0.082)	(0.059)	(0.074)	(0.057)
Sex * positive rainfall in year 1	0.045	0.032	0.040	0.029
	(0.083)	(0.060)	(0.080)	(0.060)
Sex * positive rainfall in year -1	0.075	-0.006	0.080	-0.004
	(0.074)	(0.061)	(0.072)	(0.060)
Sex of child	-0.136	-0.014	-0.134	-0.014
	(0.093)	(0.070)	(0.091)	(0.069)
Observations	10592	10592	10592	10592
R^2	0.199	0.251	0.213	0.259

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
The sample used is children aged 1-3 year old children in the Demographic and Health Survey 1998-99.
The regressions include month or season of birth and district fixed effects. Also includes controls for birth order, preceding birth interval, dummy for child received any vaccine, number of sister and brothers under 13 of the parents and in the household, age and sex of household head, wealth index quintile, age, age square, height and weight of mother, years of schooling of mother and father, dummy for mother working on farm, categorical variable for occupation of father, religion and caste. Village level control variables are village electrification, traditional attendant in village, population in village, distance to all weather road, health sub centre and community health centre.
The regressions include district fixed effects. SOB refers to season of birth and MOB refers to the month of birth.

Positive rainfall is wet season rainfall greater than 20th percentile.

Table 4: Impact of Rainfall Shocks on crop yield

	(Wheat)	(Rice)	(Jowar)	(Maize)	(Bajra)
Positive rainfall in wet season	0.054***	0.149***	0.058***	0.065***	0.059***
	(0.012)	(0.013)	(0.009)	(0.017)	(0.010)
Observations	7317	7317	7317	7317	7317
R^2	0.710	0.691	0.502	0.424	0.299

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
The sample consists of information on Indian districts between 1956 and 1987 from the World Bank Agriculture and Climate Data.
Positive rainfall is wet season rainfall greater than 20th percentile.

The regressions include district fixed effects and controls for other agricultural inputs (fertilizers, labor, bullocks and machines), population density and literacy of males in the district.

Table 5: Time use (in hours) of 15-30 year old women- by season

	Oct/Nov	Feb	Apr/May
Agriculture	2.27	2.09	2.09
	(3.13)	(3.02)	(3.05)
Market work	0.73	0.76	0.76
	(1.65)	(1.67)	(1.67)
Household work	6.93	6.87	6.95
	(2.90)	(2.81)	(2.85)
Fuel+water	1.51	1.52	1.48
	(1.57)	(1.62)	(1.62)
Leisure	7.39	7.61	7.62
	(2.40)	(2.39)	(2.39)
Obs	3933	3962	3928

Standard deviation in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
The sample used is 15-30 year old women interviewed in Rural Economic and Demographic Survey 1998-99.

Table 6: Impact of rainfall on time use in October-November (period of harvesting wet season crops) of women 15-30 years old with children under 2

	(Rain in quintiles)				(Continuous rain measure)			
	(Agriculture)	(Market)	(Household)	(Fuel+water)	(Agriculture)	(Market)	(Household)	(Fuel+water)
Positive rainfall in wet season of 1998	0.045	0.008	0.126	-0.120				
	(0.219)	(0.118)	(0.224)	(0.194)				
Positive rainfall					0.028	-0.034	0.147	-0.005
					(0.064)	(0.036)	(0.092)	(0.056)
Negative rainfall					-1.057*	0.368***	0.467	-0.526
					(0.545)	(0.110)	(0.339)	(0.341)
Owns land dummy	-0.657***	0.400***	0.508***	-0.285***	-0.652***	0.394***	0.523***	-0.278***
	(0.127)	(0.087)	(0.128)	(0.097)	(0.126)	(0.088)	(0.127)	(0.096)
HH income (Rs. 000')	-0.002**	0.000	0.003***	-0.002***	-0.002**	0.000	0.003***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of living children	-0.008	-0.016	-0.062*	0.066**	-0.008	-0.017	-0.059*	0.068***
	(0.027)	(0.022)	(0.035)	(0.025)	(0.027)	(0.021)	(0.035)	(0.025)
Years of schooling of woman	-0.029***	0.007	0.051***	-0.038***	-0.028***	0.007	0.051***	-0.038***
	(0.010)	(0.009)	(0.013)	(0.008)	(0.010)	(0.009)	(0.013)	(0.008)
Years of schooling of husband	-0.009	0.009	0.003	-0.005	-0.009	0.008	0.004	-0.004
	(0.011)	(0.007)	(0.010)	(0.007)	(0.011)	(0.007)	(0.010)	(0.007)
Age of husband	0.010	0.003	-0.007	-0.002	0.010	0.003	-0.006	-0.002
	(0.012)	(0.007)	(0.013)	(0.007)	(0.012)	(0.007)	(0.012)	(0.007)
Age of woman	0.012	0.001	-0.020	0.013	0.012	0.002	-0.023	0.013
	(0.015)	(0.010)	(0.020)	(0.010)	(0.015)	(0.010)	(0.019)	(0.010)
Observations	3933	3933	3933	3933	3933	3933	3933	3933
R^2	0.543	0.247	0.384	0.165	0.543	0.247	0.386	0.164

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
The sample consists of women aged 15-30 years interviewed in Rural Economic and Demographic Survey 1998-99.
Positive rainfall is wet season rainfall greater than 20th percentile. For continuous rainfall measures, refer to subsection 9.2 in Appendix.
Agriculture includes working on family farm and wage work. Market work includes non-agricultural wage work and self employment as well as salaried work.
The regressions include state fixed effects. Also includes controls for dummy for land ownership, household income, number of living children, marital status, years of schooling of woman and her husband, age of woman and her husband, categorical variable for occupation of woman, her husband, religion and caste

Table 7: Impact of Rainfall Shocks on duration of breastfeeding- using Cox's proportional hazard model

	(Girl)	(Boy)
Positive rainfall	-0.035	-0.168
	(0.144)	-0.168
Birth Order	-0.381***	-0.387***
	(0.061)	(0.072)
preceding birth interval	-0.001	-0.004
	(0.003)	(0.003)
Observations	49999	57233

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
The sample used is children aged 0-3 year old children in the Demographic and Health Survey 1998-99 for whom breastfeeding stopped in the wet season.
Positive rainfall is wet season rainfall greater than 20th percentile.

The regressions include season of birth and district fixed effects. Also includes controls for birth order, preceding birth interval, mother currently pregnant, number of sister and brothers under 13 of the parents and in the household, age and sex of household head, wealth index quintile, age and age square of mother, height and weight of mother, years of schooling of mother and father, dummy for mother working on farm, categorical variable for occupation of father, religion and caste. Village level control variables are village electrification, traditional attendant in village, population in village, distance to all weather road, health sub centre and community health centre.

Table 8: Impact of Rainfall Shocks on health outcomes- categorized by state

	(HAZ score)		(WAZ score)	
	(Girl)	(Boy)	(Girl)	(Boy)
Panel 1: Rich states				
Positive rainfall in utero	0.127	0.061	-0.037	0.114
	(0.244)	(0.247)	(0.151)	(0.173)
Positive rainfall in year 1	0.258	0.205	0.056	0.207
	(0.313)	(0.297)	(0.223)	(0.191)
Positive rainfall in year 2	-0.614	-0.162	-0.532*	-0.255
	(0.400)	(0.263)	(0.291)	(0.222)
Positive rainfall in year 3	-0.156	0.274	-0.376	0.022
	(0.356)	(0.268)	(0.268)	(0.204)
Positive rainfall in year 4	0.016	0.230	0.028	-0.015
	(0.270)	(0.245)	(0.221)	(0.197)
Observations	992	1187	992	1187
R^2	0.285	0.277	0.324	0.344
Panel 2: Poor states				
Positive rainfall in utero	0.421***	0.345***	0.259***	0.158**
	(0.132)	(0.114)	(0.098)	(0.077)
Positive rainfall in year 1	0.597***	0.460***	0.506***	0.327***
	(0.149)	(0.153)	(0.103)	(0.104)
Positive rainfall in year 2	0.187	0.184	0.159	0.173
	(0.205)	(0.189)	(0.163)	(0.123)
Positive rainfall in year 3	-0.241	-0.208	-0.093	-0.057
	(0.249)	(0.186)	(0.179)	(0.132)
Positive rainfall in year 4	-0.155	0.023	-0.049	0.063
	(0.202)	(0.148)	(0.160)	(0.105)
Observations	2462	2693	2462	2693
R^2	0.213	0.194	0.257	0.262

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
The sample used is children aged 1-3 year old children in the Demographic and Health Survey 1998-99.
Positive rainfall is wet season rainfall greater than 20th percentile.
The richest states include Punjab, Haryana, Goa, Himachal Pradesh, Gujarat, Jammu and Maharashtra. The poorest states include Bihar, Assam, Madhya Pradesh, Orissa, Rajasthan and Uttar Pradesh

The regressions include season of birth and district fixed effects. Also includes controls for birth order, preceding birth interval, dummy for child received any vaccine, number of sister and brothers under 13 of the parents and in the household, age and sex of household head, wealth index quintile, age, age square, height and weight of mother, years of schooling of mother and father, dummy for mother working on farm, categorical variable for occupation of father, religion and caste. Village level control variables are village electrification, traditional attendant in village, population in village, distance to all weather road, health sub centre and community health centre.

Table 9: Impact of Rainfall Shocks on health outcomes- categorized by household wealth

	(HAZ score)		(WAZ score)	
	(Girl)	(Boy)	(Girl)	(Boy)
Panel 1: Bottom 40 pctile on wealth index				
Positive rainfall in utero	0.346**	0.348***	0.195*	0.161*
	(0.143)	(0.127)	(0.102)	(0.091)
Positive rainfall in year 1	0.505***	0.405**	0.431***	0.205*
	(0.160)	(0.167)	(0.107)	(0.113)
Positive rainfall in year 2	0.386*	0.180	0.355**	0.139
	(0.199)	(0.193)	(0.152)	(0.131)
Positive rainfall in year 3	-0.025	0.001	-0.059	0.089
	(0.248)	(0.215)	(0.181)	(0.134)
Positive rainfall in year 4	0.027	0.173	-0.002	0.113
	(0.202)	(0.174)	(0.151)	(0.117)
Observations	2409	2464	2409	2464
R^2	0.251	0.253	0.297	0.302
Panel 2: Top 60 pctile on wealth index				
Positive rainfall in utero	-0.006	-0.010	0.021	-0.019
	(0.157)	(0.159)	(0.105)	(0.114)
Positive rainfall in year 1	0.110	0.165	0.081	0.215*
	(0.186)	(0.166)	(0.133)	(0.122)
Positive rainfall in year 2	-0.037	-0.008	-0.160	-0.065
	(0.212)	(0.173)	(0.144)	(0.124)
Positive rainfall in year 3	0.068	0.145	0.062	-0.007
	(0.217)	(0.168)	(0.145)	(0.126)
Positive rainfall in year 4	0.150	0.235	0.242*	0.168
	(0.198)	(0.152)	(0.135)	(0.115)
Observations	2668	3051	2668	3051
R^2	0.315	0.279	0.346	0.316

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
The sample used is children aged 1-3 year old children in the Demographic and Health Survey 1998-99.
Positive rainfall is wet season rainfall greater than 20th percentile.
The regressions include season of birth and district fixed effects. Also includes controls for birth order, preceding birth interval, dummy for child received any vaccine, number of sister and brothers under 13 of the parents and in the household, age and sex of household head, wealth index quintile, age, age square, height and weight of mother, years of schooling of mother and father, dummy for mother working on farm, categorical variable for occupation of father, religion and caste. Village level control variables are village electrification, traditional attendant in village, population in village, distance to all weather road, health sub centre and community health centre.

Table 10: Impact of Rainfall Shocks on health outcomes- categorized by mother's education

	(HAZ score)		(WAZ score)	
	(Girl)	(Boy)	(Girl)	(Boy)
Panel 1: Mother has schooling				
Positive rainfall in utero	0.057	0.006	-0.071	0.081
	(0.165)	(0.140)	(0.118)	(0.126)
Positive rainfall in year 1	0.052	0.208	0.028	0.122
	(0.193)	(0.152)	(0.137)	(0.138)
Positive rainfall in year 2	-0.028	0.204	-0.220	0.082
	(0.208)	(0.184)	(0.135)	(0.131)
Positive rainfall in year 3	-0.051	0.176	-0.115	0.080
	(0.228)	(0.189)	(0.150)	(0.155)
Positive rainfall in year 4	0.049	0.152	0.110	0.088
	(0.191)	(0.151)	(0.138)	(0.131)
Observations	2186	2435	2186	2435
R^2	0.350	0.296	0.388	0.326
Panel 2: Mother has no schooling				
Positive rainfall in utero	0.283**	0.281**	0.166*	0.075
	(0.130)	(0.121)	(0.097)	(0.079)
Positive rainfall in year 1	0.525***	0.294*	0.377***	0.245**
	(0.145)	(0.163)	(0.100)	(0.102)
Positive rainfall in year 2	0.216	0.030	0.216	0.035
	(0.193)	(0.181)	(0.132)	(0.118)
Positive rainfall in year 3	0.166	0.068	0.153	-0.001
	(0.209)	(0.187)	(0.148)	(0.115)
Positive rainfall in year 4	0.266	0.269	0.223*	0.138
	(0.179)	(0.172)	(0.129)	(0.107)
Observations	2893	3080	2893	3080
R^2	0.244	0.222	0.287	0.278

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
The sample used is children aged 1-3 year old children in the Demographic and Health Survey 1998-99.
Positive rainfall is wet season rainfall greater than 20th percentile.
The regressions include season of birth and district fixed effects. Also includes controls for birth order, preceding birth interval, dummy for child received any vaccine, number of sister and brothers under 13 of the parents and in the household, age and sex of household head, wealth index quintile, age, age square, height and weight of mother, years of schooling of mother and father, dummy for mother working on farm, categorical variable for occupation of father, religion and caste. Village level control variables are village electrification, traditional attendant in village, population in village, distance to all weather road, health sub centre and community health centre.

9 APPENDIX

	Kharif			Rabi			Total	
Year	Area	Prod.	%	Area	Prod.	%	Area	Prod.
1991-92	78.02	91.59	54.39	43.85	76.79	45.61	121.87	168.38
1992-93	77.92	101.47	56.54	45.23	78.01	43.46	123.15	179.48
1993-94	75.81	100.40	54.49	46.94	83.86	45.51	122.75	184.26
1994-95	75.19	101.09	52.79	48.67	90.41	47.21	123.86	191.50
1995-96	73.60	95.12	52.72	47.42	85.30	47.28	121.02	180.42
1996-97	75.34	103.92	52.11	48.24	95.52	47.89	123.58	199.44
1997-98	74.15	101.58	52.83	49.70	90.68	47.17	123.85	192.26
1998-99	73.99	102.91	50.55	51.18	100.69	49.45	125.17	203.60
1999-00	73.24	105.51	50.29	49.87	104.29	49.71	123.11	209.80
2000-01	75.22	102.09	51.87	45.83	94.73	48.13	121.05	196.81
2001-02	74.23	112.07	52.65	48.55	100.78	47.35	122.78	212.85
2002-03	68.56	87.22	49.91	45.30	87.55	50.09	113.86	174.77
2003-04	75.44	117.00	54.88	48.01	96.19	45.12	123.45	213.19
2004-05	72.26	103.31	52.08	47.82	95.05	47.92	120.08	198.36
2005-06	72.72	109.87	52.67	48.88	98.73	47.33	121.60	208.60

Area in million hectares, production in million tonnes

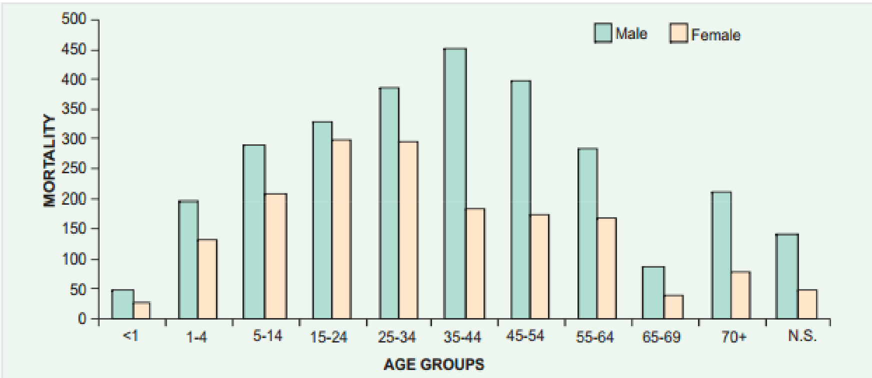
Source: Directorate of Economics and Statistics, Ministry of Agriculture, Government of India

Figure 5: Season-wise Area, Production and Yield of Foodgrains from1991-92 to 2005-06

9.1 Inverse Distance Weighting

This is a popular measure of calculating the point precipitation of a district from multiple weather stations. Each observed weather station value is given a unique weight based on the distance from the centroid of the district in question. The district precipitation value is then calculated based on the weighted sum of each observed weather station precipitation value.[7] Below is a diagrammatic illustration from the National Weather Service website:

[7] National Weather Service website



Source:(Dash, 2009), Figures presented for every thousand persons. N.S. = not specified

Figure 6: Age and Sex distribution of malaria mortality in India in 1998

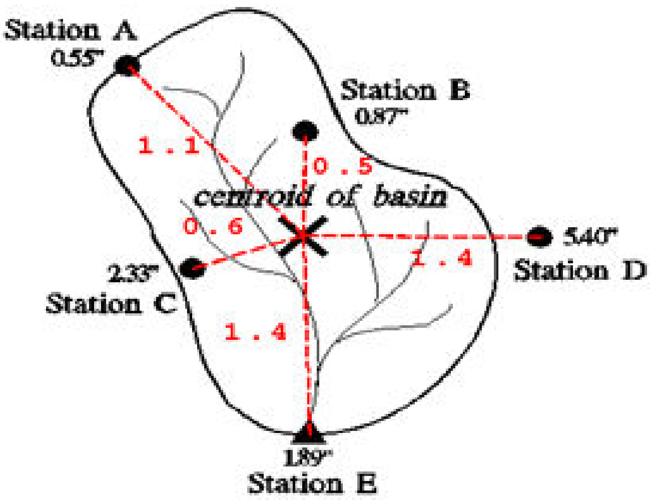


Figure 7: Evolution of child (0-4 years) sex ratio in India at the district level

9.2 Measure of rainfall shock

An additional measure of rainfall that we construct is continuous and captures the deviation of rainfall in each wet season (and also separately dry season) around birth in the district in which the child is born from the district's 40 year historical wet season (and dry season) mean excluding the year in which the child is born, normalized in terms of standard deviation. The wet season variable is graphed in Figure 8 by gender. It ranges from -1.41 to 6.55. The distribution shows that the probability of being born in a district with negative (or positive) rainfall deviation is the same for boys and girls. It also shows that there were no 'big' droughts during this time period (in the districts that are covered by DHS 1998-99).

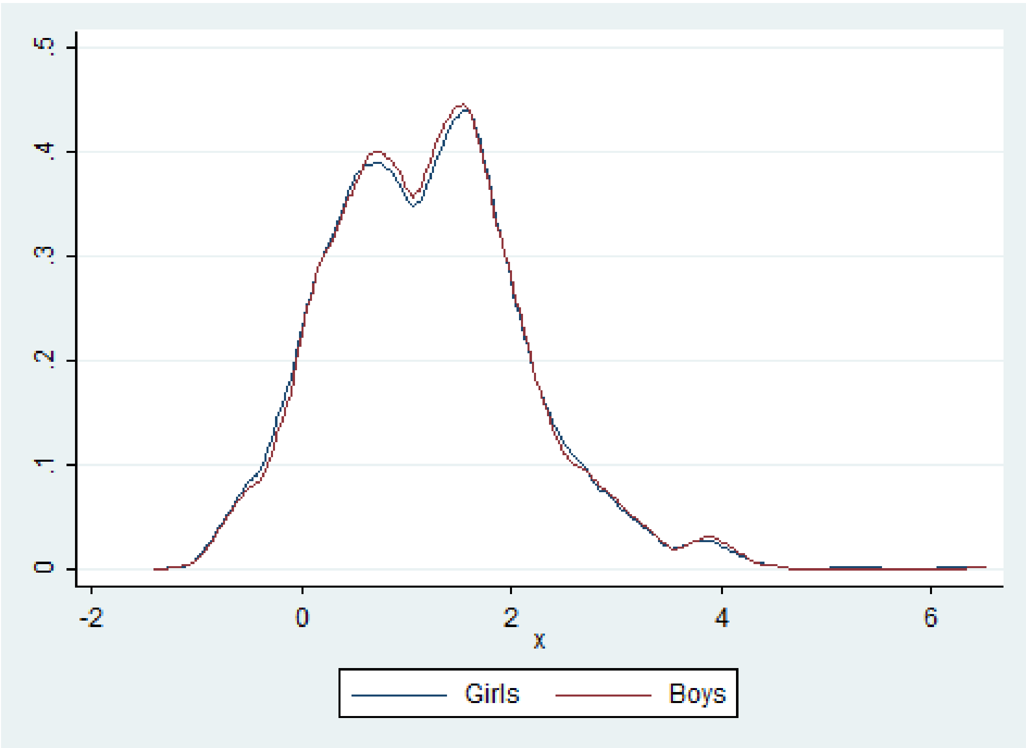


Figure 8: Distribution of deviation of wet season rainfall from historical mean, standardized

Another measure of rainfall that I use is categorical. I calculate for each district, the historical mean (the 40 year wet season mean), historical mean minus one standard deviation, historical mean plus one standard deviation. Then, I assigned rainfall shock to each child equal: 0 (negative rainfall) if wet season rainfall around his/her birth is less than 'historical mean less 1 standard deviation'; 1 (normal rainfall) if wet season rainfall around his/her birth lies between 'historical mean less 1 standard deviation' and 'historical mean plus 1 standard deviation'; and 2 (positive deviation) if wet season rainfall around his/her birth is greater than 'historical mean plus 1 standard deviation'.

Table A-1: Sample used from DHS 1998-99

	Frequency	Percent
Total living children	31690	100
Out of which:		
Sick/ refused/ not present	6876	21.70
Urban area	6770	21.36
Age less than 12 months	45.51	21.16
Other variables missing	745	2.35
Number of children used for analysis	10592	33.42

Table A-2: Sample used from REDS 1998-99

	Frequency	Percent
Total women interviewed	10501	100
Out of which:		
Duplicates	68	0.65
Women greater than 30 years of age 6017	57.30	
Other variables missing	483	4.60
Number of women used for analysis	3933	37.45

Table A-3: Impact of Rainfall Shocks on health outcomes- using different measures of rainfall shock

	(HAZ)		(WAZ)		(HAZ)		(WAZ)	
	(Girl)	(Boy)	(Girl)	(Boy)	(Girl)	(Boy)	(Girl)	(Boy)
Positive deviation from mean in year 1-wet	0.123**	0.087*	0.070*	0.064*				
	(0.057)	(0.048)	(0.040)	(0.038)				
Negative deviation from mean in year 1-wet	-0.439	-0.356	-0.371*	-0.432**				
	(0.300)	(0.330)	(0.206)	(0.186)				
Positive deviation from mean in utero-wet	0.029	0.019	0.020	0.021				
	(0.055)	(0.051)	(0.040)	(0.038)				
Negative deviation from mean in utero-wet	-0.306	-0.278	-0.185	-0.087				
	(0.290)	(0.227)	(0.224)	(0.154)				
1.Categorical rainfall measure in year 1					0.440***	0.430***	0.365***	0.265***
					(0.115)	(0.127)	(0.073)	(0.079)
2.Categorical rainfall measure in year 1					0.439***	0.385**	0.326***	0.252**
					(0.149)	(0.159)	(0.095)	(0.105)
1.Categorical rainfall measure in utero					0.314***	0.266**	0.170**	0.077
					(0.121)	(0.114)	(0.085)	(0.077)
2.Categorical rainfall measure in utero					0.119	0.071	0.064	0.005
					(0.133)	(0.144)	(0.096)	(0.099)
Observations	5077	5515	5077	5515	5077	5515	5077	5515
R^2	0.244	0.226	0.290	0.284	0.245	0.228	0.292	0.285

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
The sample used is children aged 1-3 year old children in the Demographic and Health Survey 1998-99.
Refer to subsection 9.2 in Appendix for more information on rainfall measures.
The regressions include season of birth and district fixed effects. Also includes controls for birth order, preceding birth interval, dummy for child received any vaccine, number of sister and brothers under 13 of the parents and in the household, age and sex of household head, wealth index quintile, age, age square, height and weight of mother, years of schooling of mother and father, dummy for mother working on farm, categorical variable for occupation of father, religion and caste. Village level control variables are village electrification, traditional attendant in village, population in village, distance to all weather road, health sub centre and community health centre.

Table A-4: Impact of Rainfall Shocks on health outcomes- detailed result

	(HAZ score)		(WAZ score)	
	(Girl)	(Boy)	(Girl)	(Boy)
Positive rainfall in utero	0.232**	0.205**	0.124*	0.086
	(0.105)	(0.093)	(0.074)	(0.066)
Positive rainfall in year 1	0.369***	0.317***	0.283***	0.215***
	(0.119)	(0.113)	(0.081)	(0.080)
Positive rainfall in year 2	0.176	0.133	0.092	0.069
	(0.143)	(0.122)	(0.101)	(0.081)
Positive rainfall in year 3	0.081	0.137	0.032	0.044
	(0.169)	(0.132)	(0.111)	(0.091)
Positive rainfall in year 4	0.172	0.213*	0.172*	0.129*
	(0.138)	(0.110)	(0.100)	(0.078)
Birth Order	-0.005	-0.032	-0.038	-0.053***
	(0.028)	(0.028)	(0.024)	(0.020)
Preceding birth interval	0.001	0.002*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Received vaccine dummy	0.022	0.083	0.031	0.044
	(0.094)	(0.087)	(0.058)	(0.058)
Number of sisters under 13	-0.136***	0.033	-0.062*	0.031
	(0.042)	(0.036)	(0.033)	(0.029)
Number of brothers under 13	-0.076*	-0.010	-0.017	0.016
	(0.040)	(0.040)	(0.032)	(0.030)
Number of boys under 13 in HH	0.015	0.007	0.010	0.007
	(0.014)	(0.014)	(0.011)	(0.009)
Number of girls under 13 in HH	0.000	-0.005	-0.009	-0.007
	(0.015)	(0.013)	(0.011)	(0.009)
Sex of HH Head-male	0.151*	-0.157	0.066	-0.006
	(0.083)	(0.099)	(0.069)	(0.074)
Age of HH Head	-0.000	-0.003	-0.000	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Wealth Score	0.204***	0.175***	0.150***	0.164***
	(0.047)	(0.050)	(0.042)	(0.040)
Age of mother	0.014	0.024	0.002	0.032
	(0.040)	(0.033)	(0.030)	(0.026)
Age of mother sq	-0.000	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Education of mother (in years)	0.022***	0.041***	0.024***	0.031***
	(0.008)	(0.008)	(0.007)	(0.006)
Mother's weight	0.012***	0.015***	0.032***	0.030***
	(0.004)	(0.004)	(0.003)	(0.003)
Mother's height	0.043***	0.040***	0.019***	0.018***
	(0.005)	(0.005)	(0.004)	(0.004)
Mom works on farm	0.021	-0.011	0.013	-0.044
	(0.065)	(0.066)	(0.048)	(0.047)
Education of father (in years)	0.017**	0.004	0.014***	0.005
	(0.007)	(0.007)	(0.005)	(0.005)
Electrified village with irregular supply	-0.092	0.046	0.082	0.105
	(0.113)	(0.120)	(0.092)	(0.071)
Electrified village with regular supply	-0.138	0.033	0.034	0.048
	(0.130)	(0.116)	(0.107)	(0.076)
Traditional attendant in village	0.060	0.038	0.029	0.052
	(0.064)	(0.057)	(0.046)	(0.041)
Population of village	0.001	-0.005	0.002	-0.005
	(0.006)	(0.005)	(0.005)	(0.004)
Distance to all weather road	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to health sub centre	-0.001	-0.002	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Distance to community health centre	-0.002	-0.001	-0.002*	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	5077	5515	5077	5515
R^2	0.244	0.227	0.291	0.284

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
The sample used is children aged 1-3 year old children in the Demographic and Health Survey 1998-99.
Positive rainfall is wet season rainfall greater than 20th percentile.
The regressions include season of birth and district fixed effects. Also includes controls for categorical variable for occupation of father, religion and caste.

Table A-5: Comparison of DHS and REDS surveys

	DHS	REDS	Difference
HH size	7.07	7.17	0.10
	(3.50)	(3.81)	
Hindu HH	0.86	0.89	0.03***
	(0.35)	(0.31)	
Sex of head	0.95	0.95	0.01
	(0.22)	(0.21)	
Age of head	45.51	47.40	1.89***
	(15.88)	(15.31)	
Obs	21976	3635	25611

Standard deviation in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
The sample has been restricted to households where women in the age of 15-30 years were interviewed in both surveys.

9.3 Note on Cox proportional hazard model

Survival and duration models originated in biomedical sciences; where the interest lies in observing time to death of patients or laboratory animals or until the relapse of an illness. In the recent past however, these techniques have increasingly become popular in social sciences. Here, I summarize the method.

Let the random variable T denote survival time. The distribution function of T is defined by the following equation and indicates the probability of death up until time t

$$F(t) = P(T < t)$$

The survival function S(t) denotes the probability of surviving until time t or longer and is given by

$$S(t) = P(T \geq t) = 1 - F(t)$$

The limit of S(t) represents the risk or proneness to death at time t. This limit is usually called the hazard function which measures the death rate given survival until time t.

In this data, we have information on the number of months the child has been breastfed and whether he/ she is still being breastfed. Since our data is right censored, we model the relationship between rainfall shocks and breastfeeding duration using a multivariate hazard model as this technique adjusts for truncation bias by incorporating both complete and incomplete segments of histories in the analysis of breastfeeding-related data. In our case thus, the hazard function measures the risk of stoppage of being breastfed at time t as a result of a rainfall shock around that period, given that the child has been breastfed until time t and a set of characteristics X.

We then estimate this relationship using Cox's proportional hazard model which uses parametric specification to estimate the relationship between hazard rates and covariates- a log partial likelihood function is maximized to produce maximum partial likelihood estimates of the model parameters. The advantage of using Cox's partial likelihood model is that it allows the derivation of estimates of the slope coefficients within the vector betas from a proportional hazard model, but places no restrictions at all on the shape of the baseline hazard.